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Job Sorting in African Labor Markets

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Abstract

Using matched employer-employee data from eleven African countries, we investigate if there is job sorting in African labor markets. We find that much of the wage gap correlated with education is driven by selection across occupations and firms. This is consistent with educated workers being more effective at complex tasks like labor management. In all countries the education wage gap widens rapidly at high low levels of education. Most of the education wage gap at low levels of education can be explained by selection across occupations.

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1. Introduction

Much attention has been devoted to human capital and its role in development (e.g. Lucas 1993, Mankiw, Romer & Weil 1992). Microeconomic studies have consistently shown that education and earnings are positively correlated, at least in activities such as manufacturing and modernized agriculture (e.g. Jamison & Lau 1982, Knight & Sabot 1990, Yang 1997, Fafchamps 1999). But little remains known about how labor markets in poor countries identify and reward skills, experience, and schooling. At some basic level, a key role of the labor market is to provide individuals and firms with the best possible opportunity to maximize the value of output, in terms of earnings and profits, given the available inputs (like human and physical capital). The premise of this paper is that how much a worker can contribute to output may depend on which job the worker has, in which case the labor market has a potentially important role to play in ensuring that the allocation of workers to jobs is as efficient as possible. It is well known that if worker and firm productivity are complements, the labor market solution to the allocation problem may result in sorting, i.e. that productive firms primarily form relationships with productive workers (Becker 1973). The main purpose of this paper is to investigate empirically if there is sorting in Africa labor markets, a continent for which very little is known about how firms and employees form working relationships.

In order to establish how firm and worker characteristics correlate, access to matched employer-employee data is necessary. In recent years researchers have gained access to several large matched employer-employee data-sets from developed countries, which has benefitted the empirical research on worker-firm relationships substantially (Abowd, Kramarz & Margolis 1999). Unsurprisingly, for developing countries data-sets of this nature are much harder to come by. As far as we know, the largest and most comprehensive matched employer-employee data-set from Africa is that used by Fafchamps and Söderbom (2006) in their study of labor management and wages in the continent. In this paper we update these data and add Algeria to the sample of countries, thereby generating a data-set spanning 11 countries and more than 30,000 employees.[1] We focus on the manufacturing sector, because most firms in this sector are privately owned and follow a for-profit motive.[2]

Our main null hypothesis is that there is no sorting in African labor markets. This is firmly rejected by the data. A large share – about a third – of the education wage gap comes from selection across occupations. Another third takes place through selection across firms. At low levels of education, most of the wage gap occurs via selection across occupations. There is also a large gender wage gap in all studied countries, women earning on average less than men. A large proportion of this wage gap is explained by selection into low wage occupations and firms. We also find that the education wage gap tends to be higher for women, except in Morocco where many poorly educated women work in the export garment sector.

The paper is organized as follows. The conceptual framework is presented in section 2. The data sources and survey methodology are presented in section 3. Regressions of earnings functions appear in Section 4, and conclusions are provided in Section 5.

[1] As far as we know, we are the first to analyze returns to education for such a large number of African countries. Previous studies on returns to education in Africa are typically confined to one or a few countries, see e.g. Moll (1996) on South Africa; Canagarajah & Thomas (1997) on Ghana; Krishnan, Selassie & Dercon (1998) on urban Ethiopia; Appleton, Bigsten & Manda (1999) on Kenya; Appleton (2002) on Uganda; and Söderbom, Teal, Wambugu and Kahyarara (2006) on Kenya and Tanzania.

[2] Other sectors are less suited for an analysis of this type. In in the African public sector, for instance, the importance of political appointments, prebendalism, and overstaffing has long been documented. (e.g. Vijverberg 1989, Vijverberg Fall1993, Velenchik 1997*a*). Trade unions are also more active in the civil service and government-owned firms than in the private sector. The likely presence of market distortions makes it difficult to interpret the correlation between education and wages. In the fast growing not-for-profit sector, the education wage gap is similarly difficult to measure given the importance of volunteer work and the practice of hiding worker remuneration in perks and in-kind advantages (e.g. Edwards & Hulme 1995, Barr, Fafchamps & Owens 2005). Earnings are also inherently hard to measure in self-employed agriculture, which characterizes much of Africa.

2. Conceptual Framework

The main goal in this paper is to investigate if there is any evidence of 'sorting' in African labor markets, i.e. that workers with high (low) skills tend to get allocated to firms with high (low) inherent productivity. The idea that workers and firms sort according to such a process goes back a long way in economics – Roy (1951) is often taken as a starting point – and has been the basis for explaining behavior in a wide range of markets (see Becker (1973) and more recently Shimer & Smith (2000) and Shimer (2001)).

Much of the current state-of-the-art theory on labor market sorting does not generate models that are well suited for empirical analysis, however. Deriving interesting behavioral models is a complex task. To do so, researchers often have to invoke simplifying and sometimes unrealistic assumptions about workers and jobs (see the discussion in Sattinger (1993)). Furthermore, while mathematically rigorous, theoretical models in this area tend to be specific. The sorting result is a good example. Assuming that there are no frictions (e.g. search costs) and that assignment is binary (a productive relationship contains only two individuals), Becker (1973) shows that complementarities in production generates sorting in equilibrium. This results in a positive correlation between productive skills across relationships. Mortensen (2003) shows that, with constant returns to scale and search costs, this is no longer the case. He concludes that whether worker productivity and firm productivity are positively correlated is primarily an empirical question.

Our main objective is empirical in nature. Inevitably, we will venture into the 'mirky middle ground between diminishing returns and search frictions' (Mortensen, 2003, p.33) where reality lies but where the theoretical underpinnings are, at best, weak. Before doing so, it is helpful to define a point of departure where theory and empirics have some common ground. Abowd, Kramarz, Lengermann & Perez-Duarte (2004) propose a useful (albeit highly stylized) framework to this end. These authors start from the Becker (1973) model and write the output given by matching worker i with firm j as Cobb-Douglas:

$$Y_{ij} = q_i^{\lambda} c_j^{\upsilon},$$

where q_i denotes the worker quality, c_j is firm productivity, and λ, υ are parameters. Assuming the wage to be a fixed proportion ω of output (rent-sharing and risk neutrality are among the key assumptions here), Abowd et al. (2004) obtain a log-linear wage equation of the following form:[3]

$$\log w_{ij} = \log \omega + \lambda \log q_i + \upsilon \ln c_j \tag{2.1}$$

The relevant productivity indices are $\lambda \log q_i$ for the worker and $\upsilon \log c_j$ for the firm. Under the null hypothesis that there is no sorting, there should be no correlation between worker and firm productivity: $cov\left[\lambda \log q_i, \upsilon \log c_j\right] = 0$. This simple observation is the basis for most of our empirical work below.

2.1. Sorting between firms

To operationalize a test for sorting, we need to define the firm and worker productivity indices. Our data-set contains multiple observations on workers within firms (up to 10 employees per firm were interviewed as part of the surveys, see Section 3). This makes it possible to allow for firm fixed effects in the wage regresssions. These fixed effects control for *all* firm-level determinants of wages at a given point in time, which goes a long way in solving potential omitted variables problems. Further, at the firm level there is a panel dimension, which means the firm effects

[3] Rent sharing is likely to be more prevalent when the labor market is not very flexible and workers cannot move across firms to arbitrage wage differentials. Bigsten, Collier, Dercon, Fafchamps, Gauthier, Gunning, Isaksson, Oduro, Oostendorp, Patillo, Soderbom, Teal & Zeufack (2004) and Velenchik (1997*b*) present empirical evidence suggesting that rent sharing is present in African manufacturing.

can be time-varying. These firm-time effects, denoted u_{jt} below, are taken to represent the firm productivity index.

At the worker level there is no panel dimension, but detailed information on key components of human capital exist. We focus on years of schooling, denoted S_i. We decompose the worker productivity indes $\lambda \ln q_i$ as follows:

$$\lambda \log q_i = \zeta_i + \gamma S_i,$$

where ζ_i is a skills component independent of education and γ is a parameter. By definition ζ_i and S_i are orthogonal, and so γ is interpretable as a measure of the marginal productivity of schooling combined with all unobserved individual characteristics correlated with schooling. We replace $\lambda \ln q_i$ in (2.1) by $\zeta_i + \gamma S_i$, and treat ζ_i as a residual. Adding the relevant time t, firm j and worker i subscripts, we have a wage equation of the following form:

$$\log w_{ijt} = \ln \omega_t + \gamma S_i + u_{jt} + \zeta_{ijt}.$$

Since the residual ζ_{ijt} by definition is uncorrelated with schooling, the parameter γ is *not* interpretable as a measure of the productive return to education, but to skills defined more broadly. To estimate returns to schooling, it would be necessary to purge the schooling data from all unobserved factors that impact independently on wages so as to avoid 'ability bias' (Card 2001). This is not our objective here – see Söderbom et al. (2006) for such an attempt.

It follows from the above that under the null hypothesis of no sorting, we should have $cov\left[S_i, u_{jt}\right] = 0$. To operationalize a test of this hypothesis, define

$$\log w_{ijt} = \alpha_1 H_{ijt} + \gamma_1 S_{ij} + \varepsilon_{1ijt}, \qquad \text{(model 1)}$$

$$\log w_{ijt} = \alpha_2 H_{ijt} + \gamma_2 S_{ij} + u_{2jt} + \varepsilon_{2ijt}, \qquad \text{(model 2)}$$

where H_{ijt} denotes a vector of worker characteristics other than education, included as basic control variables. Under the null hypothesis of no sorting, we have $\gamma_1 = \gamma_2$: the education wage gap is the same accross firms as it is within firms. Under the alternative hypothesis of sorting, we expect $\gamma_2 < \gamma_1$, i.e. the education wage gap should fall as a result of conditioning on firm productivity because worker productivity is positively correlated with firm productivity.

2.2. Observable tasks

The basic idea behind labor market sorting is that the realised productivity of a worker depends on which job the worker performs. In the previous section we have discussed how firm and worker productivity may be positively correlated, if 'good' workers get allocated to firms with 'good' jobs. Implicit in the argument is that the proportion of 'good' jobs varies across firms, which seems plausible: some firms offer a lot of high-return jobs, e.g. in labor management, whilst other firms predominantly offer low-return jobs, e.g. unskilled production.

However, if the productivity index of a given task somehow could be measured, a more direct test of sorting would be to examine the correlation between task productivity and worker skills. In our data-set a wide range of jobs are represented, from unskilled low-wage production jobs on the factory floor to sophisticated management jobs for which wages are not far from levels in developed countries. It seems likely that, across these occupations, tasks and productivity vary quite a lot. For instance, management jobs carry a lot of responsibility and may therefore have to pay well to compensate for higher intellectual effort, relative to basic unskilled jobs.[4] Alternatively, it could be that skilled jobs are prone to suffer from moral hazard (since output may be harder to measure), in which case the firm may find it optimal to pay efficiency wages (e.g. Shapiro & Stiglitz 1984, Sparks 1986, Azam & Lesueur 1997).

If occupation is a reasonably good proxy for tasks, we can use occupation data to go beyond simple worker-firm correlations. We use the data on occupations in two ways. First, we replace the firm effects in (model 2) by occupation dummies, denoted D_{ijt}:

$$\log w_{ijt} = \alpha_4 H_{ijt} + \gamma_4 S_{ij} + \eta_4 D_{ijt} + \varepsilon_{4ijt} \qquad \text{(model 4)}$$

As before, under the null of no sorting we have $\gamma_4 = \gamma_1$, whereas under the alternative we expect $\gamma_4 < \gamma_2$. The purpose of this approach is to obtain a test of whether individuals with a lot of education tend to get allocated to high-productivity jobs across firms. Second, we add occupation dummies to (model 2) yielding a specification that contains both firm and job effects:

$$\log w_{ijt} = \alpha_3 H_{ijt} + \gamma_3 S_{ij} + \eta_3 D_{ijt} + u_{3jt} + \varepsilon_{3ijt}. \qquad \text{(model 3)}$$

Under the null of no sorting, $\gamma_3 = \gamma_1$, i.e. the coefficient on schooling does not change as a result of adding firm effects and occupation dummies to (model 1).

Estimating models (1) to (4) is the focus of this paper. Under the null of no sorting we have $\gamma_1 = \gamma_2 = \gamma_3 = \gamma_4$. If this, our most comprehensive test for sorting, is rejected, the way in which these parameters differ can shed some light on potentially interesting economic mechanisms. If $\gamma_1 > \gamma_2$ and $\gamma_4 > \gamma_3$ this suggests that sorting across firms is more important than sorting across jobs, and hence that there is a lot of heterogeneity in tasks across firms for

[4] A related possibility is that workers in skilled jobs may need to be compensated for the disaffection from fellow workers that they incur for taking on, say, a supervisory role.

a given type of job. This would be consistent with a high opportunity costs of job search: being a qualified accountant, for instance, would not necessarily result in a high wage; but finding the right accounting job would.

Testing other hypotheses is also of interest. One could argue that one of the purposes of education is to make someone more effective at managing other workers, either directly (e.g., foreman) or indirectly (e.g., accountant). This seems plausible since literacy and numeracy skills enable workers to record and process information more effectively, and hence to organize and monitor other workers with less effort. If educated workers have a lower effort cost of supervision or are more efficient at labor management, they are more likely to be in a supervisory role. In this case, part of the education wage gap will be due to selection of better educated workers into supervisory occupations. Another way of looking at this is to say that the (financial) returns to education partly take the form of selection across occupations. In this case, we have $\gamma_1 = \gamma_2 > \gamma_3 = \gamma_4$ and $\eta_3 = \eta_4 \neq 0$.

Finally, if the data support $\gamma_1 = \gamma_2 = \gamma_3 = \gamma_4$, as well as $\eta_3 = \eta_4 = 0$, and $var\,(u_{2jt}) = var\,(u_{3jt}) = 0$, this can be interpreted as evidence that the labor market is 'perfect', that is, competitive and with full information and contract enforcement. In such a case, the education wage gap is the same accross firms as it is within firms, and workers with the same levels of education are paid the same in different occupations.

It is often argued that wage differentials across firms are due to systematic variation between firms in the unobserved productivity of their workforce (Oi & Idson 1999). This notion is closely related to the interpretation we have suggested: certain firms need good workers and hence spend more resources screening and retaining them. Educated workers are plausibly more productive in firms that require more worker supervision and labor management. Because these firms need to better motivate workers and supervisors and need to reward workers for their extra care and effort, they also tend to pay higher wages. The same kind of reasoning can be followed for occupation assignment. There is a difference between our interpretation of the education coefficients in models (1) to (4) and standard concerns about unobserved heterogeneity, but it is fairly slight: the unobserved heterogeneity argument regards worker productivity as a time-invariant trait; we regard it as driven by moral hazard and labor management considerations. But we agree on one important point: the productivity of workers varies systematically across firms in ways that are reflected in the wage they earn.

2.3. Extension I: Non-constant education wage gap

So far we have assumed that the education wage gap is linear in years of schooling. There may in fact be too restrictive. Early work in this area indicated that the earnings function is concave in education so that increases in education at low levels had relatively high returns (e.g. Psacharopoulos 1994, Psacharopoulos & Patrinos 2002). Much of the recent evidence, however, suggests that the earnings-education profile is in fact convex.[5] Aggregate growth regressions also suggest that secondary education has higher aggregate returns than primary education (Barro & i Martin 1992).

The shape of the returns to education curve has important policy implications regarding the allocation of school funding between primary, secondary, and tertiary education. There is indeed a strong relationship between the need for specific skills in the economy and the rate at which these skills are rewarded in the market place. If, for instance, what manufacturing needs most is basic literacy and numeracy skills, we would expect to observe a large productivity difference – and hence a large wage gap – between illiterate workers and those with primary

[5] Kingdon & Unni (2001) report that, for urban India, returns increase with the level of education; Duraisamy (2002) finds a similar result. Belzil & Hansen (2002) report increasing marginal returns to education in the U.S., up to grade 14. Söderbom et al. (2006) document convex earnings-education profiles in Kenyan and Tanzanian manufacturing.

schooling. If, in contrast, what manufacturing needs most are the basic academic skills acquired in secondary school, we would expect a large wage gap between workers with primary and secondary education. Finally, if what manufacturing needs is high-level vocational skills acquired in post-secondary education, we would expect a large wage gap between secondary and post-secondary graduates. The detailed curvature of the education returns function thus provides important clues about the kind of skills the economy values – and hence needs – the most.

To investigate these issues more in detail, we reestimate the model in a semi-parametric fashion by letting the coefficient of S_{ij} vary with the level of schooling. To this effect, we replace the γS_{ij} term in models 1 to 4 with education dummies $\sum_n \gamma_n M_{ijn}$ where $M_{ijn} = 1$ if $S_{ij} = n$, and 0 otherwise. We expect the difference in schooling coefficients $\gamma_{n+1} - \gamma_n$ to be largest for those skills that are most valuable to the manufacturing sector. So, for instance, if the γ_n coefficients form a concave relationship with a kink at the end of primary school, we will conclude that literacy and numeracy are the most valued skills in manufacturing. If coefficients form a concave relationship but with a kink at the end of secondary school, we will conclude that basic skills in math, writing, and the sciences are also important. If, in contrast, coefficients form a convex relationship with a kink at the end of secondary school, we will conclude that what industry needs most are high-level vocational skills acquired in post-secondary education.

The decomposition analysis used in models 1 to 4 can similarly be used to ascertain whether certain types of skills acquired in school – or correlated with schooling – raise earnings via sorting across firms or across occupation. For instance, if the coefficient of university education vanishes once we control for occupation, this means that high education affects earnings entirely through sorting across occupations.

2.4. Extension II: Gender

The decomposition approach used for education can similarly be used to investigate the magnitude and source of the gender wage gap in African manufacturing. To this effect, we introduce a gender dummy θG_{ijt} in models 1 to 4. The same decomposition applies. We also examine whether the schooling coefficients vary between men and women. To this effect, we introduce a cross-term of the form $\varphi S_{ijt} G_{ijt}$ in our regressions. This tells us whether the gender wage gap is larger at low or high levels of education. Comparing the gender wage gap between models 1 to 4 will tell us what proportion of the gap is due to sorting across occupations and across firms.

Many different explanations have been proposed to account for the gender wage gap (Altonji & Blank 1999). One of these explanations is that women employees as a group are penalized by the emphasis many of them put on parenting and elderly care. This is because female workers are more likely to be absent from work to care for a sick child or an elderly parent. For the same reason, they also are less likely to accept to work overtime and after hours.[6] As a result, the explanation goes, men are often preferred for positions of responsibility. If this interpretation is correct, women should receive a lower return to high ability because they are less likely than men to be promoted to management or supervisory positions. Hence for them the coefficient of schooling should be smaller. This also implies that when we control for sorting by occupation, the gender difference in schooling coefficient should disappear or at least decrease.

Another explanation for the gender wage gap is gender segregation, modeled after Becker's (1971) Becker (1971) work on race discrimination. Underlying this explanation is the idea that, for various reasons that we need not discuss here, employers prefer a gender-homogeneous workforce, i.e., either all male or all female. The gender wage gap then arises as a result of the

[6]Because women cannot credibly commit never to take on parenting duties or to care for an elderly parent, they may be denied promotion even when they choose work over family.

sorting of workers across firms that pay different wages. If this hypothesis is true, we expect the gender wage gap to be non-existent within firms. Consequently, the coefficient of the gender dummy should disappear once we control for firm fixed effects (model 2). It is also conceivable that gender segregation varies by occupation within firms, e.g., female typists and male drivers. If this is the cause for the gender wage gap, the coefficient of the gender dummy should no longer be significant once we control for occupation.

Gender segregation can affect the coefficient of schooling if male-dominated jobs require more schooling and ability. This occurs, for instance, if management and supervisory jobs are reserved for men while low skilled work is reserved for women. If this hypothesis is correct, the coefficient of S_{ij} should be higher for men because they get selected in higher paying occupations. In this context, the difference in schooling coefficients between men and women should disappear once we control for occupation.

Yet another possibility is that, in order to compete with men for better paid jobs, women must be more qualified than men. This can arise because employers prefer male employees and are willing to incur a cost in terms of lost productivity in order to employ them – this is Becker (1971) old 'taste for discrimination' idea. Alternatively, female workers may be victim of what Arrow (1972) called 'statistical discrimination': if the population of female workers is less productive on average or has a larger variance in unobserved ability, employers will demand higher credentials from female job applicants (Coate & Loury 1993). In this case, women will be paid less on average but those with better credentials will be able to compete with men for better paid jobs, thereby raising the schooling coefficient for female workers. In this case, controlling for occupation should narrow the gender wage gap as well as the difference in schooling coefficient between men and women. Investigating these various hypotheses is the object of the rest of the paper.

3. The Data

The data used in this paper come from a variety of surveys collected over a period spanning more than a decade. They cover two North African countries – Algeria and Morocco – and nine Sub-Saharan African (SSA) countries – Burundi, Cameroon, Cote d'Ivoire, Ethiopia, Ghana, Kenya, Tanzania, Zambia, and Zimbabwe. For many of these surveys, the authors were directly involved in the design of the questionnaire, the piloting of the surveys, and/or the training of the enumerators. They are therefore quite familiar with the surveyed firms and the strengths and weaknesses of the data.

The bulk of the data from SSA was collected as part of the Regional Program for Enterprise Development (RPED) organized by the World Bank. In this program, samples of approximately 200 randomly selected firms were interviewed in eight countries (Burundi, Cameroon, Cote d'Ivoire, Ghana, Kenya, Tanzania, Zambia, and Zimbabwe). The surveys started with Ghana in 1992, and most other country surveys were initiated in 1993.[7] Firms were re-interviewed three years in a row in most countries; as some firms dropped out of the sample, they were replaced with other firms with similar characteristics.[8] Four sectors of activity are covered: textile and garments; wood products; metal products; and food processing. Firms of all sizes are included except for microenterprises which are excluded.[9] The RPED data have been extensively analyzed and have greatly improved our understanding of manufacturing in the continent (e.g. Bigsten et al. 2000a, 2000b, 2004; Mazumdar and Mazaheri 2002).

We augment the RPED data set with data from two other sources. First, we add data

[7] RPED or RPED-style surveys have been conducted in other African countries as well, but the worker questionnaire was not used. Consequently, we do not have matched employer-employee data for these countries.

[8] Burundi was surveyed only once due to the rapid deterioration of the political situation following the Rwandan genocide. Cote d'Ivoire was surveyed only twice due to insufficient funding.

[9] The reason is that, in most SSA countries, microenterprises far outnumber other firms (e.g. Daniels 1994, Liedholm & Mead 1999). Sampling randomly from the population of all firms would have yielded samples constituted nearly exclusively of microenterprises.

on Ethiopian manufacturing firms that were collected independently of RPED but using the same questionnaire.[10] Second, we use data from the Kenyan Manufacturing Enterprise Survey (KMES), fielded in 2000 and designed as a follow-up to the last Kenyan RPED survey.[11] This survey generates data for 1998 and 1999, yielding a combined sample size of 15,712 workers.

In addition to our surveys from SSA, we have data from surveys in Algeria and Morocco. The Moroccan and Algerian questionnaires are very similar in spite of using two different acronyms.[12] Both surveys focus on enterprises employing at least 10 people and operating in the following sectors of activity: food processing (excluding bakeries), textile, garments, leather, electrical machinery, chemicals, and plastics. The Algerian data were collected in 2002 in collaboration between the government and the World Bank as part of the Investment Climate Assessment (ICA) surveys. Around 600 firms were interviewed. The Moroccan data were collected as part of the Firm Analysis and Competitiveness Surveys (FACS), carried out in 2000 jointly by the World Bank and the Ministry of Commerce, Industry and Telecommunications (Fafchamps, El Hamine & Zeufack 2002). A sample of 860 firms in the six main towns was randomly chosen from a census of manufacturers conducted every year by the Ministry. The Moroccan survey generates data for 1998 and 1999.

As already mentioned, one unusual feature of all these data sets is that they contain matched employer-employee information. At the same time as the firms were surveyed, a sample of workers was chosen from each firm designed to cover the full range of firm employees. The objective was to have up to 10 workers from each firm where firm size allowed. To increase the informational content of the data, the worker sample was stratified according to occupational status.[13] Each worker was interviewed individually by enumerators.

[10] The Ethiopian survey was coordinated by Taye Mengistae.

[11] The KMES was organized by the Centre for the Study of African Economies, University of Oxford. See Söderbom and Teal (2001) for a report based on these data.

[12] The ICA questionnaire is but an improved version of the FACS questionnaire.

[13] Where there is panel data, samples of workers have been interviewed again in subsequent years, but the

The methodology used to draw samples of workers in each firm implies that manufacturing workers did not all have the same probability of being selected. Since at most 10 workers were interviewed in each firm, workers in large firms have a lower probability of being interviewed. We correct for this in the analysis by giving workers in large firms a weight proportional to the total number of employees in the firm. Moreover, within each firm, enumerators were instructed to select workers from each occupational category. This means, for instance, that employees engaged in occupations that represent a small proportion of the workforce – such as managers and technical staff – have a higher likelihood of being interviewed than skilled and unskilled workers, who constitute the bulk of the workforce. To correct for this, we weigh each worker by the number of employees in his or her occupational category in the firm. Unless otherwise indicated, all analysis conducted in this paper corrects for stratification.

The main characteristics of the employee sample are presented in Table 1 for the 11 countries covered by this paper. To illustrate the importance of properly weighting the data, we show weighted and unweighted means for all workers characteristics.[14] If several years of data are available, all years are combined.

Average monthly earnings, expressed in US$, show remarkable variation across countries. Cameroon has weighted average earnings roughly equivalent to those in Morocco but more than five times those in Tanzania. The two CFA countries in our sample – Cameroon and Cote d'Ivoire – pay higher manufacturing wages on average than the non-CFA countries in Sub-Saharan Africa. The high wages paid in these two countries may reflect the overvaluation of the currency.

Levels of schooling of the manufacturing workforce vary much less across countries than

identity of the workers differs across survey rounds. In all surveys, information on worker identifiers was not collected to protect the confidentiality of workers' responses.

[14] The standard deviation is calculated on the unweighted data.

average earnings: with the exception of Ethiopia, Burundi and Cote d'Ivoire, in all the other countries the average manufacturing worker has around 8 years of education – the equivalent of a junior high school degree. There is no apparent relationship between average wages and average schooling levels. Manufacturing workers in Tanzania earn five times less than those in Morocco and Cameroon, even though they have basically the same education level on average. Moreover, Cote d'Ivoire pays higher wages although workers are less educated than in other studied countries. We also see few differences in average age, experience, or length of tenure across countries, the only possible exception being Burundi where workers tend to be younger, less experienced and with a shorter tenure. This probably reflects the small size of most manufacturing firms in the Burundi sample (Bigsten, Collier, Dercon, Fafchamps, Gauthier, Gunning, Isaksson, Oduro, Oostendorp, Patillo, Soderbom, Teal & Zeufack 2000).

It is rare for African manufacturers to offer vocational training to their employees. In Morocco, only 2% of manufacturing workers received vocational training from a previous employer. For SSA countries, the number of cases was so small than the question had to be dropped from the survey at pre-testing stage.

Turning to the composition of the sample by gender, we see that women account for 10 to 27% of the manufacturing workforce in SSA but for up to 50% in Morocco where they constitute the bulk of unskilled and skilled manpower in the textile and garment sectors. We find that in all countries men dominate high and middle management positions.

The breakdown by occupational category varies somewhat between countries in that the level of disaggregation used in the nine RPED surveys is more detailed than that used in Morocco and Algeria. We also see that correcting for stratification does not have a major impact on the occupational breakdown in the SSA samples but has a large effect in Morocco. This is due to the fact that Moroccan firms are larger on average than SSA firms and use relatively less management (Fafchamps and Söderbom, 2006).

Although it is not the focus of this paper, there is a striking contrast in the proportion of production workers in the total workforce. At one extreme, production workers represent 93% of the manufacturing workforce in Morocco. In contrast, in SSA, even if we include supervisors, technicians, and maintenance staff, they only represent between 51% (Tanzania) to 75% (Kenya) of the workforce, with a SSA average of 66%. As shown by Fafchamps and Söderbom (2006), some of this gap is due to differences in firm size – SSA firms tend to be smaller and smaller firms have proportionately more non-production personnel. The rest is probably due to rent sharing and labor management difficulties (e.g. Velenchik 1997*b*, Bigsten et al. 2004, Mazumdar & Mazaheri 2002).

4. Econometric results

We now turn to the estimation of earnings regressions. As pointed out earlier, all regression results presented here are weighted by the size of the firm's employment in each occupational category to correct for oversampling. We also correct standard errors for clustering and stratification.[15] Given the stratified nature of the sample, proper weighting and correcting for stratification and clustering are absolutely essential to draw correct inference.[16]

[15] Given the very large number of individual effects in some regressions, including individual dummies is not a feasible option. Fixed effect regression on suvey data is implemented by differencing the data with respect to the weighted mean.

[16] If we fail to correct for stratification, the education coefficient tends to fall somewhat. This is because large firms tend to pay better wages. Hence failing to weigh observations gives less importance to observations coming from large firms.

As discussed in Section 2, we estimate four regression models of the form:

$$\log w_{ijt} = \alpha_1 H_{ijt} + \theta_1 G_{ijt} + \gamma_1 S_{ij} + \varphi_1 S_{ijt} G_{ijt} + \varepsilon_{1ijt} \quad \text{(model 1)}$$

$$\log w_{ijt} = \alpha_2 H_{ijt} + \theta_2 G_{ijt} + \gamma_2 S_{ij} + \varphi_2 S_{ijt} G_{ijt} + u_{2jt} + \varepsilon_{2ijt} \quad \text{(model 2)}$$

$$\log w_{ijt} = \alpha_3 H_{ijt} + \theta_3 G_{ijt} + \gamma_3 S_{ij} + \varphi_3 S_{ijt} G_{ijt} + \eta_3 D_{ijt} + u_{3jt} + \varepsilon_{3ijt} \quad \text{(model 3)}$$

$$\log w_{ijt} = \alpha_4 H_{ijt} + \theta_4 G_{ijt} + \gamma_4 S_{ij} + \varphi_4 S_{ijt} G_{ijt} + \eta_4 D_{ijt} + \varepsilon_{4ijt} \quad \text{(model 4)}$$

for each of the 11 countries in our sample. For Morocco and Algeria, we have large samples so that we can comfortably estimate regressions separately for each country. Sample sizes are much smaller for Sub-Saharan Africa, unfortunately. For these countries, we increase efficiency by estimating a pooled regression in which the coefficients of worker characteristics H_{ijt} and occupation dummies D_{ijt} are constrained to be the same across countries. We do, however, allow the coefficients of the gender dummy G_{ijt}, the schooling variable S_{ijt} and their cross-term to vary across countries. We also include country dummies and, if we have multiple years for one country, year-specific country dummies.

For Morocco and Algeria, we have information on whether the worker received vocational training from a previous employer. We include this information as a dummy variable as well as a cross-term between vocational training and gender.[17] Interpretation of the results concerning this variable follows the same principles as for education.

In addition to gender, our earnings regression include the standard set of controls: age, work experience, job tenure, and their square. In the Morocco sample, we also include a dummy for whether the wage figure provided by the respondent is net of taxes. In the other countries, wages are always reported net of taxes.

[17] We also have information on vocation training received from the current employer. This variable, however, is subject to selection bias, training being offered to very bad or very good workers, and it is ignored here.

Detailed regression results for Sub-Saharan Africa are presented in Table 2 for models 1 to 4. Those for Morocco and Algeria are given in Tables 3 and 4, respectively. All regressions correct for weighting, stratification, and clustering. We begin by discussing the education wage gap. Education coefficients have been summarized in Table 5 to facilitate comparison. We then discuss vocation training before briefly commenting on the other regressors.

4.1. Education and Earnings

As is immediately apparent from the first column of Table 5 (model 1), the education wage gap in African manufacturing is rather large. Education is strongly significant in model 1 regressions in all countries. For male workers, the average education wage gap over the 11 countries is 5.9%, with a minimum of 2.7% in Ghana and a the maximum of 10.5% in Zambia. Algeria and Morocco tend to have slightly lower education wage gap than SSA.

We also observe a large gender difference in the education wage gap. On average, this gap is higher for women, with an average return of 7.5% across all 11 countries. There is, however, a marked variation across countries. In seven of the eleven countries, the gender difference is not significant at the 10% level. In three countries, the difference is significant and positive: Cote d'Ivoire, Kenya and Zimbabwe (see Table 2). In these countries the female dummy is also negative and significant. The implication is that women on average get paid less than men but the gap is lower for educated women. In these three countries, the gender wage gap disappears for women with 10 to 12 years of education. These results are consistent with the idea that women must be better educated in order to compete with men for better paid jobs, perhaps because of statistical discrimination.

In contrast, in Morocco, the gender difference in the education wage gap is negative and strongly significant. At the same time, the gender dummy is positive. Estimated coefficients indicate that above 3 years of schooling the gender wage gap becomes negative; a positive gender wage gap exists only for workers with very little education. This result is consistent with the idea that female workers in Morocco are not selected for jobs that require a high level of education.

Comparing models 1 and 2 in Table 5 tells us how much of the education wage gap is due to sorting among firms. On average across the 11 countries, the sorting of male workers across firms accounts for less than 20% of the gap. This percentage, however, varies dramatically across countries – from a high of 74% in Ghana to a low of -14% in Zimbabwe. In all countries we can reject at the 1% level the hypothesis that $\gamma_2 = 0$: the positive education wage gap for male workers is not entirely due to sorting among firms.

The picture is different for female workers. The magnitude and significance of the gender dummy fall in most countries once we control for firm fixed effects. This suggests that the gender wage gap is due in large part to sorting among firms – perhaps because of gender segregation by employers. Sorting among firms also accounts for a larger proportion of the education wage gap for women: once we control for firm fixed effects, the coefficient of schooling for women falls by a third on average over the 11 countries. Morocco again stands out as an exception, with the schooling coefficient rising for women after we control for firm fixed effects. This means that educated women tend to work in firms that on average pay less to their workforce. After controlling for selection among firms, the education wage gap is very similar for men and women – 4.8% versus 5.0% on average over the 11 countries. In model 2, the gender difference in the education coefficient is significantly positive in only two countries – Algeria and Kenya – while it is significantly negative in Morocco and Burundi.

Turning to model 3 in Table 5, we observe a further fall in the coefficient on education for male and female workers. We find that, within the same firm, workers in management positions receive wages that are 60% (Algeria) to 100% (Morocco) higher than those of skilled production workers, our reference category. Those in middle management and administrative positions receive wages on average 20% to 67% higher than those of unskilled workers while unskilled workers are paid on average 12% to 24% less than skilled workers. In all cases, Morocco displays the strongest wage differences by occupation.

Part of these differences in wage reflect differences in education since the coefficient of education in model 3 captures wages differences across workers who are in similar occupations in the same firm. On average across the 11 countries, sorting across firms and occupations accounts for over half of the total education wage gap in manufacturing. In one country, Ghana, the coefficient of schooling is no longer significant, suggesting that, in that country, sorting by firm and occupation accounts for all the education wage gap. Ghana is also the country in which the education wage gap is the lowest. In contrast, in Zimbabwe and Burundi, the schooling coefficients are virtually identical whether we control for selection or not. This suggest that there are probably large difference across countries regarding what mechanism drives returns to education and ability in manufacturing.

In Morocco, a special case in our sample as far as gender is concerned, the gender difference in the education wage gap is no longer significant in model 3. This is consistent with the idea that in that country the gender wage gap is due to women being confined to low paying firms and occupations – mostly production workers in the textile and garment sectors.

Finally we turn to model 4 in which we control for occupation but not for firm fixed effects. We see that, for male and female workers, selection among occupations accounts on average for one third of the education wage gap. Put differently, one third of the wage difference is achieved because educated workers tend to be selected in better paid occupations. Results also indicate that the wage premium paid to workers in management and administrative or support staff positions is nearly always larger when we do not control for firm fixed effect. This suggest that firms that hire more management and administrative or support staff also pay higher wages to all workers on average. This result is consisten with the observation by Fafchamps and Söderbom (2006) that larger firms in SSA and Morocco need to motivate production workers and supervisors by paying higher wages.

We have seen that a non-negligible proportion of the education wage gap is due to sorting among firms. In Section 2, we hinted that this may be due to firm size and capital-labor ratio. To investigate this hypothesis, we regress the estimated firm-level fixed effects $\widehat{u}_{jt}$ on the log of capital and employment and sectoral dummies. The estimated model is of the form:

$$\widehat{u}_{jt} = \alpha \log L_{jt} + \beta \log K_{jt} + \tau M_{jt} + \varepsilon_{jt}$$

where $\widehat{u}_{jt}$ is the estimated fixed effect for firm j in year t from model 2, L_{jt} is total employment in firm j at time t, K_{jt} is capital stock, and M_{jt} is a vector of sectoral and year dummies. To save on degrees of freedom, we again pool the SSA observations but include country-year dummies.

Results are presented in Table 6. They show that larger firms in terms of total employment (for Morocco and Algeria) and capital (all regressions) level pay higher wages to all workers. This is a standard result (Oi & Idson 1999).[18] Taken together with our earlier findings, we see that part of the education wage gap results from the fact that better educated workers are hired by firms that are larger and more capital intensive. We also find some very large sector and country dummies, suggesting that some of the wage difference across firms are related to technology.

[18] Fafchams and Söderbom (2006) investigate the reason for this relationship in African manufacturing.

4.2. Vocational training and earnings

A similar decomposition analysis can be applied to returns from vocational training, for which we have data only for Morocco and Algeria.[19] To minimize the risk of endogeneity bias, we only consider vocational training received from a previous employer, not from the current employer. Since only a small proportion of surveyed workers report receiving such training, results should be treated with caution.

We find a large vocational training wage gap in Morocco – around 37% for men and 27% for women (Table 3, model 1). The gender difference, however, is not significant – possibly because of the small number of workers who received such training. The vocation training wage gap is much lower in Algeria – 2.3% for men and 4.9% for women – and non significant.

By comparing models 1, 2 and 3 for Morocco, we see that, as in the case of education, around one fifth of the vocational training wage gap is due to sorting between firms and one third to sorting across occupations. It therefore appears that returns to vocational training manifest themselves in ways similar to those of education and ability.

4.3. Tenure, age and experience

Tables 2 to 4 also provide valuable information regarding returns to work experience and length of tenure, as well as the age profile of manufacturing wages. Since these variables are used here primarily as controls, we only describe them briefly.

We begin with the relationship between wages and years of tenure, summarized in the first panel of Table 7 for various values of tenure. In model 1 (first column) we find the usual declining marginal returns to tenure for the Sub-Saharan Africa manufacturing firms but constant returns in Algeria and increasing returns in Morocco. This, however, arises because of a strong positive

[19] Vocational training is so rare in Sub-Saharan manufacturing that questions relative to vocational training were eventually dropped from the worker questionnaire.

relationship between length of tenure and average firm wage: firms that pay better wages also retain workers longer. This is immediately apparent by comparing results for models 1 and 2: once we control for unobserved firm heterogeneity (model 2), all three samples display the usual falling marginal returns to length of tenure. The effect appears strongest in Morocco which, as we have seen, also has the widest wage disparity across occupation categories. Within firms, some of the returns to tenure are obtained by promotion across occupational categories – most commonly, from unskilled to skilled production worker. Indeed, marginal returns to tenure fall in most cases once we control for occupation (model 3).

Turning to age (second panel of Table 7), we find different patterns across the three samples. In Sub-Saharan Africa, the estimated coefficients generate strong, declining returns to age. Some of these returns take the form of selection across firms: once we control for unobserved firm heterogeneity, returns to age fall, suggesting that firms that pay more on average also tend to employ younger workers. One possible explanation is that firms that pay more are those seeking to hire more workers; consequently, they are also the firms that hire younger, less experienced workers. We find that returns to age fall once we control for occupation, a finding consistent with the idea that, as they age, SSA workers get promoted to better paid occupational categories.

The pattern is similar for Algeria except that wages increase more slowly with age and even appear to fall for older workers. Once we control for firm heterogeneity, the marginal age effect becomes larger, suggesting that firms that pay more on average employ old workers. One possible explanation is rent seeking: firms with an older, more established workforce have had more time to be subjected to more rent seeking and thus pay higher wages.

Morocco displays yet another pattern whereby the marginal effect of age on earnings increases with age. We do not have an explanation for this unusual result, except to point out that returns to experience are falling strongly in Morocco as well. Since by construction the age and experience variables are closely related, it is possible that the Moroccan result is due to multicollinearity.

Results regarding experience suggest negative returns to experience in Sub-Saharan Africa (Third panel of Table 7). These results, however, should not be taken too seriously. The worker surveys did not collect information on years of experience directly. As in many empirical analyses of this kind, the variable 'years of experience' is constructed as the number of years since the worker left school. This is not an unreasonable assumption in the African case because many workers cannot afford to withdraw from the labor force. Still, experience is measured with error and for this reason, we do not further discuss returns to experience. More informative is the coefficient of the 'first job' dummy variable collected in Morocco, which shows a significant 5% wage penalty associated with the first job.

5. Non-parametric estimation

The results presented so far demonstrate that a large fraction of the education wage gap arises through sorting among firms and occupations. What these results do not clarify, however, is whether sorting affects the wage gap from different levels of education differently. To elucidate this point, we now turn to a non-parametric approach. In this approach, we replace the variable 'years of education' with yearly dummies and reestimate all four models. Estimated coefficients are presented graphically together with 95% confidence intervals.

Given the smaller number of available observations for Sub-Saharan Africa, we divide the data into three sub-groups: West Africa (Cameroon, Cote d'Ivoire, and Ghana), poor East Africa (Burundi, Ethiopia and Tanzania) and southern Africa plus Kenya (Kenya, Zambia and Zimbabwe). These groupings are partly based on geography, partly on levels of development. Of the three groups, the second is by far the poorest. The West African countries in our sample tend to be better off. The third group is made of intermediate countries in our African sample. Results for the three groups are presented in Figures 1, 2 and 3. Figures 4 and 5 present estimate education coefficients for Algeria and Morocco, respectively.

We focus first on coefficient estimates from model 1. From the Figures, we see that the primary education dummies are seldom significantly different from zero in Sub-Saharan and Moroccan manufacturing, the only exceptions being a mildly significant coefficient for 2 years of primary education in the West African group (Figure 1) and 5 years of primary education in the third SSA group (Figure 3) and in Morocco (Figure 5). In contrast, we find significantly positive coefficients to primary education in Algeria, although the effect is not significant for two years of primary education. These results suggest that, with the exception of Algeria, basic literacy and numeracy skills, by themselves, are not particularly crucial for African manufacturing. This is not entirely surprising, given that most manufacturing is concentrated in light industries like textile and garment where the use of sophisticated machinery is rare.

In contrast, the coefficients of post-secondary education dummies are very high in all regressions, particularly in Sub-Saharan Africa, although the shape of the curve varies a lot between regressions. In Morocco, Algeria and the third SSA group (Kenya, Zambia and Zimbabwe – Figure 3), the curve follows a relatively straightforward pattern, rising steadily above 8 years of schooling – and even accelerating markedly above 12 years of education in Morocco. This suggests that, in these countries, basic academic skills in math and English/French and high-level vocational skills are useful to the manufacturing sector.

The structure of the education wage gap curve is more complex in the first two SSA groups (Figures 1 and 2). There, we observe a sharp absolute decline in the education coefficient at and around the end of secondary school. This seems to imply that students have an incentive to stop their education halfway through secondary school; staying longer in school appears to lower their wage in absolute terms, unless they manage to complete a college degree. This interpretation may be misleading, however, because the earnings functions estimate here are conditional on workers being in manufacturing. It is conceivable that completion of secondary school opens the door to civil service jobs where pay is better. Given the data at our disposal, we cannot pursue this possibility further.

Turning to model 2, we see that in all cases the education coefficient curves shift downwards. This confirms that a large share of the education wage gap come from selection across firms. For Algeria and Morocco, once we control for unobserved firm heterogeneity schooling variables become non-significant for up to 9 years of schooling. This means that the education wage gap as lower levels of education (primary and lower secondary) results entirely from selection across firms. A somewhat similar result is observed in Figure 3, albeit with up to 7 years of schooling only. The situation is different in Figures 1 and 2. In our West African sample (Figure 1), controlling for firm heterogeneity does not change fundamentally the education coefficient curve. In the poorer countries of the sample (Figure 2), controlling for firm heterogeneity eliminates the downward 'blip' if the curve around completion of secondary school. This suggests that the firms that absorb a disproportionate share of upper secondary school leavers pay on average lower wages. One possible interpretation is that these firms serve a labor absorptive role in economies characterized by massive unemployment among school leavers (e.g. Jones 1998, Serneels 1999).

We now consider model 3. As anticipated, we note a further downward shift in the education coefficient curve in all regressions. This again confirms that a proportion of the education wage gap takes the form of selection across occupations. The same general conclusion obtains if we consider model 4. We note a fall in the education wage gap at higher education levels, suggesting that selection across occupations accounts for a larger share of education wage gap among post-secondary graduates. This interpretation is confirmed if we compare models 1 and 4. In this case, the coefficients of lower education dummies remain by and large unchanged while those of higher education dummies fall. The education wage gap between 9 and 13 years of schooling (end of secondary school) thus manifest itself primarily through better chances of obtaining middle management and support staff positions.

The results presented here suggest that returns to basic literacy and numeracy are not particularly strong in African manufacturing. Moreover, a large share of the wage gap at lower education levels comes from selection across firms, in the sense that firms paying more to all workers attract a disproportionate share of workers with some primary education. Within firms, workers tend to the paid the same irrespective of their years of primary and lower secondary education. This suggests that lower education simply serves as a screening mechanism: better paying firms probably insist on some primary education as a way of selecting high productivity workers – possibly because basic literacy and numeracy skills facilitate labor management, possibly because it signals higher ability. Conditional on being recruited in the firm, however, primary education is not rewarded. Put differently, it does not appear that basic literacy and numeracy are important to the success of African manufacturing. This interpretation is confirmed by observing that Morocco, which is by far the most successful manufacturing exporter in our sample, employs many illiterate and poorly educated workers in its competitive export sector (Fafchamps 2006).

In contrast, basic academic skills and vocational high level skills are highly rewarded in the labor market, generating in general a convex curve with an inflection point around middle school. Furthermore, we find that a large share of the wage gap for higher education workers comes from selection across occupations. This suggests that higher education is valued because it imparts skills that are valuable in management and administrative positions.

6. Conclusion

We have estimated the education wage gap in African manufacturing using employer-employee matched data on eleven countries. Results indicate that this gap can be divided into three parts: sorting across firms, sorting across occupations within firms, and the rest from higher wages paid to better educated workers in the same firm and occupation. On average across the 11 countries, sorting across firms accounts for one fifth of education wage gap while sorting across occupations accounts roughly for one third. This suggests that most of the effect of human capital on earnings operates through job selection.

In most studied countries, workers with less than completed primary education are paid the same as uneducated workers. Sorting by occupation affects primarily the coefficient of high levels of education in the earnings regression (i.e., above 9th grade). In contrast, sorting across firm affects all education levels but, in most countries, accounts for all education wage gap for workers below 9th grade. A similar pattern is observed for vocation training received from previous employers.

As anticipated, we observe a significant gender wage gap. Once we control for firm heterogeneity, the magnitude and significance of the gender dummy fall in most countries, suggesting that the gender wage gap is due in large part to sorting among firms – perhaps because of gender segregation by employers. While on average the education wage gap is higher for women, in seven of the eleven countries the difference is not significant. In three of the remaining countries, the difference is significant and positive but the female dummy is negative and significant: women on average get paid less than men but the gap is lower for educated women – and even disappears for women with 10 to 12 years of education. This suggests that women must be better educated in order to compete with men for better paid jobs, perhaps because of statistical discrimination.

Morocco, which is the country in our sample with the largest share of female employment in manufacturing, displays another pattern. The gender difference in the education coefficient is negative and strongly significant while the gender dummy is positive. The net effect is positive only for women with very little education. At higher levels of education, women get paid less than men. Furthermore, in this country we find that the gender difference in the education coefficient is no longer significant once we control for occupation and firm heterogeneity. This is consistent with the idea that in Morocco the gender wage gap is due to women being confined to low paying firms and occupations – mostly production workers in the textile and garment sectors.

Other results are also of interest. Returns to experience are shown to be large. Job specific experience has a larger effect on earnings than general work experience. But there is a large earnings penalty for first job holders. We have information regarding vocational training received in a previous job for workers in Algeria and Morocco. We find that workers who received training in their previous job earn a significantly higher wage. The effect is particularly large in Morocco.

The pattern of relationship between wages and education is indicative of the way by which human capital raises productivity. There are firms that require better educated workers on the shop floor. They are probably looking for workers with a primary or lower secondary education (e.g., up to 9th grade). These firms pay more to all workers, which suggests that they are more productive. They also tend to be larger and more capital intensive. Other firms – especially small ones – hire workers with little or no education, many of them women, and pay them lower wages.

An immediate implication of these observations is that the size distribution of firms and the relative importance of high productivity and low productivity firms within the manufacturing sector have a major effect on returns to human capital. One possible interpretation is that it is only the larger, more productive firms that can put to good use the skills workers learn in primary and lower secondary school. Alternatively, high paying firms may rely on primary and lower secondary schooling as a screening device: relative to illiterate production workers, workers with some education are likely to have higher ability on average. We suspect that the second explanation is the correct one. Indeed, once we control for firm heterogeneity, wages are the same for workers with or without primary education. In contrast, if low-level education raised worker productivity in high paying firms, they would be paid more and this would show up in the education coefficient.

A different pattern is observed for higher levels of education, i.e., upper secondary and post-secondary. For workers at this level of qualification, the education wage gap comes primarily from selection in better paid occupations, i.e., management and record keeping tasks. This is in agreement with our initial expectations: educated workers are essential to certain tasks such as labor management, record keeping, and machinery operation and maintenance. What the analysis tells us is that the level of education necessary for these tasks is quite high – above 9th grade. More work is needed to ascertain the respective roles that labor management and machine operation play in firm productivity. In particular, do educated workers raise firm productivity because they help better manage other workers or because they help better manage the machinery? Fafchamps and Söderbom (2006) examine the role of labor management in raising productivity. They conclude that labor management plays a critical and largely underestimated role. These issues deserve more research.

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Table 1. Descriptive statistics

	Kenya (N=5092)			Burundi (N=319)			Ivory Coast (N=1319)		
	sample mean	*weighted mean*	*standard deviation*	*sample mean*	*weighted mean*	*standard deviation*	*sample mean*	*weighted mean*	*standard deviation*
Monthly earnings (US$)	92.9	86.8	77.5	95.8	98.0	92.0	158.1	158.4	98.3
Years of education	8.8	8.6	3.1	4.8	4.9	5.0	5.9	6.0	4.1
Age	34.3	33.6	9.5	32.1	31.3	9.4	35.3	34.7	8.4
Years of tenure	8.2	7.5	7.4	5.4	4.8	6.3	7.7	6.9	6.7
Years of experience	17.1	16.5	10.5	15.8	14.7	10.8	18.1	17.4	9.6
Female	14.2%	14.6%		10.3%	11.9%		8.5%	10.0%	
Management	5.0%	4.2%		0.9%	0.2%		4.2%	4.9%	
Administration	10.7%	11.4%		13.2%	17.6%		12.4%	18.4%	
Commercial / Sales	3.9%	4.9%		10.3%	13.8%		4.7%	7.0%	
Supervisor	10.8%	10.9%		2.2%	2.7%		5.5%	6.0%	
Technician	2.3%	2.5%		0.0%	0.0%		5.1%	5.4%	
Maintenance	3.0%	4.3%		3.1%	2.7%		3.0%	3.1%	
Skilled production	38.0%	33.6%		69.6%	62.1%		35.0%	28.2%	
Unskilled production	15.0%	12.1%		0.0%	0.0%		24.3%	20.6%	
Apprentice	0.4%	0.8%		0.0%	0.0%		0.1%	0.1%	
Craft	7.1%	11.1%		0.0%	0.0%		0.8%	0.7%	
Support staff	3.9%	4.3%		0.6%	0.8%		4.9%	5.6%	
	Ethiopia (N=1192)			**Cameroon (N=1664)**			**Zambia (N=2476)**		
	sample mean	*weighted mean*	*standard deviation*	*sample mean*	*weighted mean*	*standard deviation*	*sample mean*	*weighted mean*	*standard deviation*
Monthly earnings (US$)	99.8	95.3	88.5	283.6	274.2	204.9	111.0	102.0	91.6
Education (years)	6.4	6.5	3.1	8.7	8.7	3.9	7.4	7.2	2.1
Age	30.6	29.7	10.8	34.2	33.9	7.5	34.1	33.8	9.7
Years of tenure	7.0	6.1	7.1	6.6	6.2	6.1	6.7	6.3	6.7
Years of experience	12.7	11.8	11.1	14.9	14.5	8.7	16.0	15.8	10.4
Female	27.3%	26.9%		14.0%	14.9%		19.3%	19.6%	
Management	2.7%	2.4%		8.5%	8.1%		11.6%	10.2%	
Administration	7.7%	10.9%		17.8%	20.3%		14.3%	13.5%	
Commercial / Sales	6.1%	8.6%		5.7%	6.2%		7.2%	8.0%	
Supervisor	4.7%	4.2%		5.8%	5.1%		13.7%	15.9%	
Technician	2.4%	2.1%		6.1%	6.5%		2.5%	2.7%	
Maintenance	1.1%	0.5%		3.7%	3.5%		2.2%	2.8%	
Skilled production	51.6%	50.7%		44.4%	42.9%		18.5%	19.9%	
Unskilled production	16.0%	13.6%		1.6%	1.3%		21.7%	18.6%	
Apprentice	2.0%	2.5%		0.2%	0.2%		0.0%	0.0%	
Craft	0.0%	0.0%		2.3%	2.7%		3.4%	4.4%	
Support staff	5.6%	4.5%		3.7%	3.1%		5.0%	4.0%	
	Tanzania (N=1462)			**Zimbabwe (N=1117)**			**Ghana (N=1934)**		
	sample mean	*weighted mean*	*standard deviation*	*sample mean*	*weighted mean*	*standard deviation*	*sample mean*	*weighted mean*	*standard deviation*
Monthly earnings (US$)	52.0	52.1	48.0	130.4	135.2	91.3	78.2	75.4	59.9
Education (years)	8.2	8.2	3.3	8.2	8.3	2.5	9.7	9.5	3.4
Age	35.4	34.7	10.1	36.8	36.2	10.5	34.3	34.0	10.1
Years of tenure	8.0	7.3	7.1	10.3	9.5	8.1	7.0	6.9	6.8
Years of experience	17.4	17.0	11.0	20.1	19.5	11.3	16.4	16.4	10.6
Female	21.9%	23.1%		15.7%	18.0%		19.6%	21.8%	
Management	18.6%	20.9%		3.1%	4.7%		7.3%	5.1%	
Administration	13.7%	17.5%		9.0%	17.3%		14.3%	16.6%	
Commercial / Sales	3.7%	5.1%		4.2%	8.2%		3.1%	4.2%	
Supervisor	6.7%	6.4%		13.4%	13.0%		10.0%	11.1%	
Technician	3.8%	4.1%		0.7%	1.5%		3.0%	3.7%	
Maintenance	3.2%	4.0%		3.0%	4.5%		2.0%	2.0%	
Skilled production	30.7%	23.3%		21.8%	14.8%		35.5%	29.9%	
Unskilled production	8.6%	9.8%		36.9%	25.0%		16.2%	18.0%	
Apprentice	0.0%	0.0%		0.8%	0.6%		0.0%	0.0%	
Craft	2.7%	3.0%		2.3%	3.1%		6.5%	8.1%	
Support staff	8.3%	5.9%		4.6%	7.2%		2.0%	1.2%	
	Morocco (N=15700)			**Algeria (N=)**					
	sample mean	*weighted mean*	*standard deviation*	*sample mean*	*weighted mean*	*standard deviation*			
Monthly earnings (US$)	328.3	270.8	373.0						
Years of education	8.7	7.9	5.4						
Age	34.7	33.2	8.8						
Years of tenure	7.2	7.0	6.4						
Years of experience	18.7	18.0	11.1						
Female	39.3%	50.5%							
Received training in previ	2.4%	1.6%							
First job	40.7%	44.1%							
Wage reported net of tax	34.8%	31.5%							
Upper management	4.5%	0.3%							
Middle management	9.3%	1.5%							
Skilled workers	39.6%	50.1%							
Unskilled worker	30.4%	43.3%							
Suppor and administrativ	16.2%	4.8%							
Second year	52.5%	53.5%							

Note: standard deviations are based on unweighted data.

Table 2. Earnings regressions in Sub-Saharan manufacturing

		model 1		model 2		model 3		model 4	
Nobs		16155		16155		16155		16155	
R-squared (within)		0.530		0.203		0.331		0.591	
Education	unit	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat
Kenya	years	0.060	**13.37**	0.037	**10.56**	0.023	**7.08**	0.037	**9.78**
Burundi	years	0.091	**9.93**	0.092	**13.26**	0.085	**12.00**	0.080	**8.64**
Ivory	years	0.043	**8.25**	0.032	**8.31**	0.013	**3.58**	0.021	**4.26**
Ethiopia	years	0.082	**8.12**	0.067	**9.31**	0.043	**6.80**	0.058	**6.34**
Cameroon	years	0.054	**12.00**	0.043	**12.11**	0.027	**7.63**	0.037	**8.68**
Zambia	years	0.105	**12.44**	0.074	**9.03**	0.034	**4.91**	0.058	**7.36**
Tanzania	years	0.051	**7.20**	0.046	**6.52**	0.013	**2.15**	0.024	**3.69**
Zimbabwe	years	0.042	**3.50**	0.048	**5.83**	0.041	**5.52**	0.031	**2.95**
Ghana	years	0.027	**3.11**	0.010	**2.14**	0.005	1.11	0.018	**2.06**
Female dummy variable									
Kenya	yes=1	-0.499	**-4.61**	-0.362	**-4.92**	-0.263	**-4.15**	-0.354	**-3.53**
Burundi	yes=1	0.169	0.78	0.184	0.96	0.200	0.99	0.151	0.72
Ivory	yes=1	-0.382	**-2.36**	-0.270	-1.49	-0.392	**-2.16**	-0.511	**-3.07**
Ethiopia	yes=1	-0.422	**-3.21**	-0.307	**-3.18**	-0.348	**-3.92**	-0.420	**-3.01**
Cameroon	yes=1	0.007	0.04	0.095	0.84	0.030	0.30	-0.062	-0.44
Zambia	yes=1	-0.110	-0.58	-0.054	-0.38	-0.256	**-1.72**	-0.281	-1.35
Tanzania	yes=1	-0.273	**-2.29**	-0.171	**-1.81**	-0.159	**-1.98**	-0.239	**-2.23**
Zimbabwe	yes=1	-0.641	**-1.74**	0.056	0.31	-0.001	-0.01	-0.648	**-1.95**
Ghana	yes=1	-0.298	**-2.32**	0.038	0.52	-0.045	-0.64	-0.350	**-2.62**
Female x education									
Kenya	years	0.043	**3.81**	0.034	**4.59**	0.022	**3.49**	0.025	**2.40**
Burundi	years	-0.025	-1.29	-0.033	**-2.09**	-0.038	**-2.35**	-0.032	-1.64
Ivory	years	0.039	**2.19**	0.031	1.58	0.042	**2.07**	0.047	**2.57**
Ethiopia	years	0.018	1.09	0.005	0.37	0.008	0.64	0.012	0.69
Cameroon	years	0.004	0.25	-0.010	-0.86	-0.006	-0.57	0.002	0.15
Zambia	years	0.030	1.26	0.016	0.90	0.037	**1.90**	0.045	1.68
Tanzania	years	0.012	0.88	0.003	0.26	0.003	0.29	0.007	0.56
Zimbabwe	years	0.061	**1.73**	-0.008	-0.40	-0.012	-0.63	0.050	1.59
Ghana	years	0.010	0.76	-0.007	-1.03	-0.001	-0.18	0.014	1.01
Worker characteristics									
Age	years	0.089	**12.77**	0.057	**11.61**	0.043	**9.81**	0.073	**10.85**
Age squared	years squ	-0.001	**-8.54**	0.000	**-6.55**	0.000	**-5.84**	-0.001	**-7.85**
Work experience	years	-0.016	**-4.56**	-0.009	**-3.81**	-0.004	**-1.88**	-0.010	**-2.87**
Work experience squared	years squ	0.000	0.78	0.000	-0.13	0.000	-1.02	0.000	0.07
Length of job tenure	years	0.016	**5.61**	0.009	**4.08**	0.006	**3.10**	0.013	**4.90**
Job tenure squared	years squ	0.000	**-1.73**	0.000	-0.81	0.000	-0.41	0.000	-1.66
Occupation codes (top management is the omitted category)									
Management	yes=1					0.679	**32.46**	0.728	**23.64**
Administration	yes=1					0.221	**14.35**	0.364	**15.77**
Commercial / Sales	yes=1					0.127	**5.91**	0.215	**6.45**
Supervisor	yes=1					0.287	**17.34**	0.391	**15.64**
Technician	yes=1					0.250	**8.84**	0.359	**9.40**
Maintenance	yes=1					0.132	**6.00**	0.255	**7.13**
Unskilled production	yes=1					-0.124	**-7.16**	-0.070	**-2.71**
Apprentice	yes=1					-0.498	**-7.02**	-0.265	**-2.15**
Craft	yes=1					0.039	**1.74**	0.143	**4.78**
Support staff	yes=1					-0.206	**-9.16**	-0.103	**-3.37**
Country dummies		yes		n.a.		n.a.		yes	
Country x year dummies		yes		n.a.		n.a.		yes	
Firm x year fixed effects		no		yes		yes		no	

Note: all regressions weighted by worker population in each firm and occupation. Standard errors corrected for clustering by firm and stratification by occupation.

Table 3. Earnings regressions in Moroccan manufacturing

		model 1		model 2		model 3		model 4	
Nobs		13700		13700		13615		13615	
R-squared (within)		0.319		0.264		0.486		0.471	
	unit	Coef.	t-stat.	Coef.	t-stat.	Coef.	t-stat.	Coef.	t-stat.
Education	years	0.045	**10.84**	0.039	**7.01**	0.015	**5.32**	0.027	**7.80**
Female	yes=1	0.070	**2.06**	0.000	-0.01	-0.074	**-3.08**	-0.022	-0.75
Female x education		-0.023	**-5.90**	-0.014	**-4.80**	-0.003	-1.21	-0.010	**-3.05**
Received training from previous e	yes=1	0.371	**4.69**	0.290	**5.20**	0.165	**2.80**	0.239	**4.33**
Female x training		-0.097	-0.85	-0.141	**-2.05**	-0.101	-1.39	-0.029	-0.28
Worker characteristics									
Age	years	-0.013	-0.95	-0.004	-0.45	-0.004	-0.75	-0.009	-1.09
Age squared	years squ	0.000	**1.73**	0.000	**2.12**	0.000	**1.88**	0.000	1.18
Work experience	years	0.016	**3.04**	0.015	**2.82**	0.012	**4.50**	0.016	**4.27**
Work experience squared	years squ	0.000	**-3.20**	0.000	**-5.18**	0.000	**-5.72**	0.000	**-3.22**
Length of job tenure	years	0.012	**2.31**	0.018	**5.52**	0.014	**5.20**	0.012	**2.50**
Job tenure squared	years squ	0.000	1.56	0.000	**-1.82**	0.000	-1.27	0.000	1.63
First job	yes=1	-0.049	**-2.02**	-0.049	**-3.30**	-0.048	**-3.91**	-0.063	**-3.13**
Wage reported net of taxes	yes=1	-0.134	**-5.53**	-0.116	**-2.99**	-0.084	**-2.48**	-0.134	**-6.14**
Occupation codes (skilled worker is omitted category)									
Upper management	yes=1					1.026	**25.03**	1.030	**17.72**
Middle management	yes=1					0.671	**23.85**	0.841	**20.49**
Unskilled worker	yes=1					-0.242	**-19.11**	-0.207	**-8.79**
Suppor and administrative staff	yes=1					-0.027	-1.28	0.095	**2.85**
Current year	yes=1	0.014	0.61	n.a.		n.a.		0.014	0.66
Firm x year fixed effects		not included		included		included		not included	
Intercept		7.336	**43.36**					7.616	**62.30**

Note: all regressions weighted by worker population in each firm and occupation. Standard errors corrected for clustering by firm and stratification by occupation.

Table 4. Earnings regressions in Algerian manufacturing

		model 1		model 2		model 3		model 4	
Nobs		6448		6448		6448		6448	
R-squared (within)		0.314		0.271		0.346		0.383	
	unit	Coef.	t-stat.	Coef.	t-stat.	Coef.	t-stat.	Coef.	t-stat.
Education	years	0.052	**10.34**	0.036	**9.70**	0.018	**5.37**	0.030	**7.82**
Female	yes=1	-0.189	**-3.02**	-0.243	**-5.62**	-0.217	**-4.92**	-0.196	**-3.59**
Female x education		0.003	0.57	0.007	**2.25**	0.007	**1.98**	0.004	1.02
Received training from previous e	yes=1	0.023	0.54	-0.001	-0.04	-0.015	-0.52	0.002	0.07
Female x training		0.026	0.34	0.021	0.35	0.035	0.69	0.027	0.41
Worker characteristics									
Age	years	0.021	**2.41**	0.024	**3.10**	0.022	**3.13**	0.015	**1.73**
Age squared	years squ	0.000	**-2.71**	0.000	**-2.63**	0.000	**-2.74**	0.000	**-2.20**
Work experience	years	0.014	**2.91**	0.006	1.52	0.004	1.03	0.012	**2.70**
Work experience squared	years squ	0.000	0.44	0.000	0.32	0.000	0.13	0.000	-0.29
Length of job tenure	years	0.006	**1.98**	0.014	**5.35**	0.012	**4.71**	0.006	**2.32**
Job tenure squared	years squ	0.000	0.00	0.000	**-2.51**	0.000	**-2.33**	0.000	-0.27
First job	yes=1	-0.037	**-1.99**	-0.043	**-2.25**	-0.044	**-2.36**	-0.043	**-2.44**
Occupation codes (skilled worker is omitted category)									
Upper management	yes=1					0.623	**14.77**	0.575	**10.68**
Middle management	yes=1					0.220	**12.46**	0.268	**7.26**
Unskilled worker	yes=1					-0.143	**-7.33**	-0.187	**-5.61**
Suppor and administrative staff	yes=1					-0.053	**-3.09**	-0.067	**-2.76**
Current year	yes=1	0.050	**2.22**					0.054	**2.68**
Firm x year fixed effects		not included		included		included		not included	
Intercept		8.248	**60.96**					8.670	**63.43**

Note: all regressions weighted by worker population in each firm and occupation. Standard errors corrected for clustering by firm and stratification by occupation.

Table 5. Education Wage Gap in African Manufacturing

		Model 1	Model 2	Model 3	Model 4
Algeria	Men	5.2%	3.6%	1.8%	3.0%
	Women	5.5%	4.3%	2.5%	3.5%
Burundi	Men	9.1%	9.2%	8.5%	8.0%
	Women	6.5%	5.9%	4.8%	4.8%
Cameroon	Men	5.4%	4.3%	2.7%	3.7%
	Women	5.8%	3.3%	2.1%	3.9%
Cote d'Ivoire	Men	4.3%	3.2%	1.3%	2.1%
	Women	8.2%	6.4%	5.4%	6.8%
Ethiopia	Men	8.2%	6.7%	4.3%	5.8%
	Women	10.0%	7.2%	5.0%	7.0%
Ghana	Men	2.7%	1.0%	0.5%	1.8%
	Women	3.7%	0.3%	0.4%	3.2%
Kenya	Men	6.0%	3.7%	2.3%	3.7%
	Women	10.4%	7.1%	4.5%	6.2%
Morocco	Men	4.5%	3.9%	1.5%	2.7%
	Women	2.1%	2.5%	1.2%	1.7%
Tanzania	Men	5.1%	4.6%	1.3%	2.4%
	Women	6.3%	4.9%	1.6%	3.1%
Zambia	Men	10.5%	7.4%	3.4%	5.8%
	Women	13.5%	9.0%	7.1%	10.3%
Zimbabwe	Men	4.2%	4.8%	4.1%	3.1%
	Women	10.3%	4.1%	3.0%	8.1%

Table 6. Regressing firm fixed effects on firm characteristics

		Morocco		**Algeria**		**SSA**	
Regression		1425		666		2753	
R-squared		0.142		0.109		0.540	
	unit	Coef.	**t-stat.**	Coef.	**t-stat.**	Coef.	**t-stat.**
Capital	log	0.043	**6.21**	0.010	**1.79**	0.000	0.09
Labor	log	0.048	**4.92**	0.038	**2.78**	0.117	**12.92**
Sector dummies		included		included		included	
Year dummies		included		included		n.a.	
Country x year dummies		n.a.		n.a.		included	
Country dummies		n.a.		n.a.		included	

Table 7. Returns to age, experience, and tenure

A. Tenure

	Years	model 1	model 2	model 3	model 4
SSA	1	1.5%	0.9%	0.6%	1.3%
	10	1.2%	0.8%	0.6%	1.0%
	20	0.9%	0.7%	0.5%	0.7%
	30	0.6%	0.6%	0.5%	0.4%
Morocco	1	1.2%	1.8%	1.4%	1.2%
	10	1.7%	1.4%	1.2%	1.7%
	20	2.3%	0.9%	1.0%	2.3%
	30	2.9%	0.5%	0.8%	2.9%
Algeria	1	0.6%	1.3%	1.2%	0.6%
	10	0.6%	1.1%	0.9%	0.6%
	20	0.6%	0.8%	0.7%	0.5%
	30	0.6%	0.5%	0.4%	0.5%

B. Age

	Years	model 1	model 2	model 3	model 4
SSA	20	5.8%	4.0%	2.9%	4.6%
	30	4.3%	3.1%	2.3%	3.2%
	40	2.7%	2.2%	1.6%	1.9%
	50	1.1%	1.4%	0.9%	0.5%
Morocco	20	0.2%	0.5%	0.1%	-0.3%
	30	0.9%	0.9%	0.4%	-0.1%
	40	1.6%	1.4%	0.7%	0.2%
	50	2.3%	1.8%	1.0%	0.5%
Algeria	20	0.9%	1.4%	1.2%	0.6%
	30	0.4%	0.8%	0.7%	0.1%
	40	-0.2%	0.3%	0.2%	-0.3%
	50	-0.8%	-0.2%	-0.3%	-0.7%

C. Experience

	Years	model 1	model 2	model 3	model 4
SSA	1	-1.6%	-0.9%	-0.4%	-1.0%
	5	-1.5%	-0.9%	-0.4%	-1.0%
	10	-1.5%	-0.9%	-0.5%	-1.0%
	15	-1.4%	-0.9%	-0.5%	-0.9%
Morocco	1	1.5%	1.4%	1.2%	1.5%
	5	1.2%	1.1%	1.0%	1.3%
	10	0.8%	0.8%	0.7%	1.1%
	15	0.4%	0.5%	0.4%	0.8%
Algeria	1	1.4%	0.6%	0.4%	1.2%
	5	1.4%	0.7%	0.4%	1.2%
	10	1.5%	0.7%	0.4%	1.2%
	15	1.5%	0.7%	0.4%	1.2%

Figure 1: Earnings-Education Profiles in Ivory Coast, Cameroon and Ghana – Models 1-4

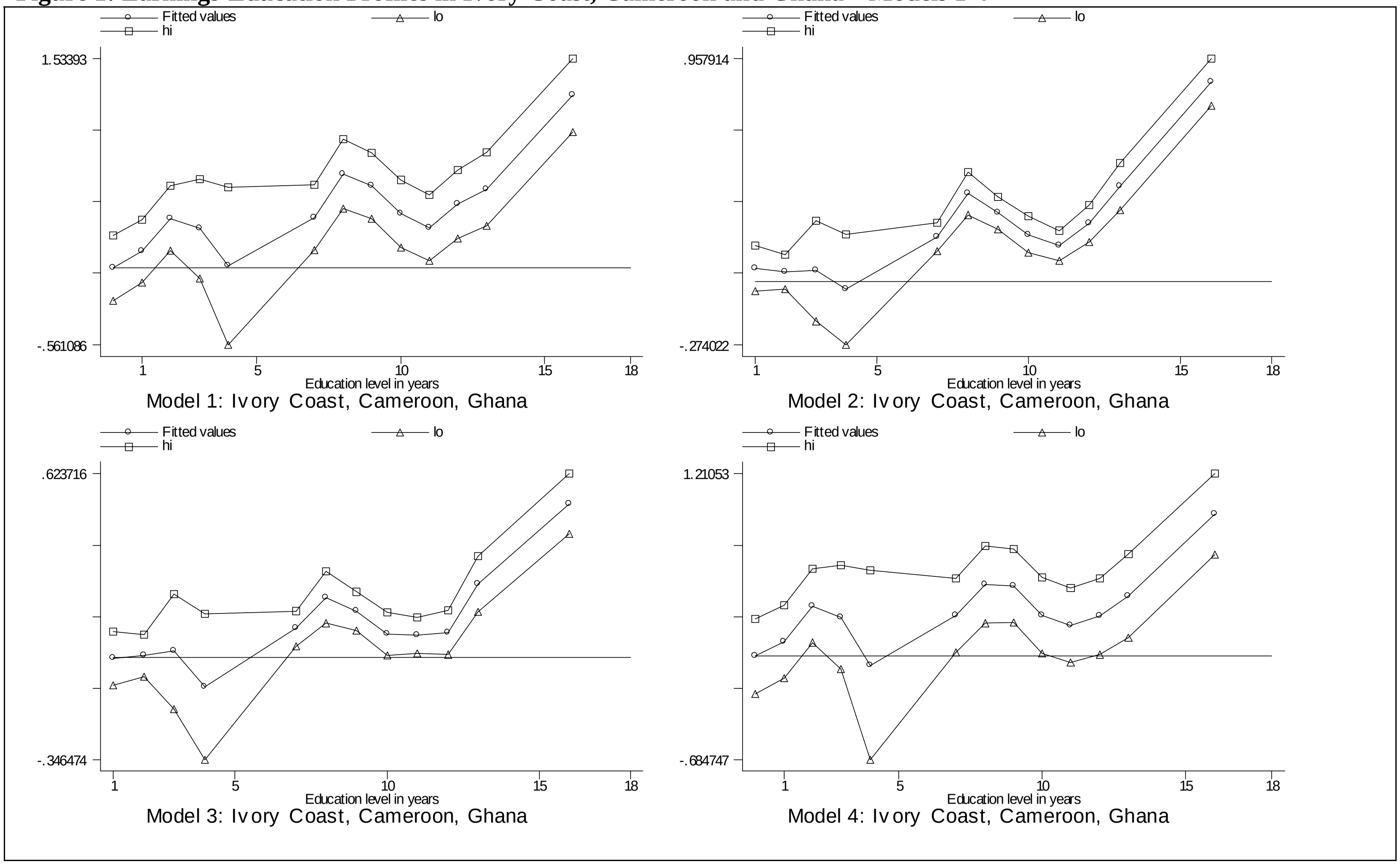


Figure 2: Earnings-Education Profiles in Burundi, Ethiopia and Tanzania – Models 1-4

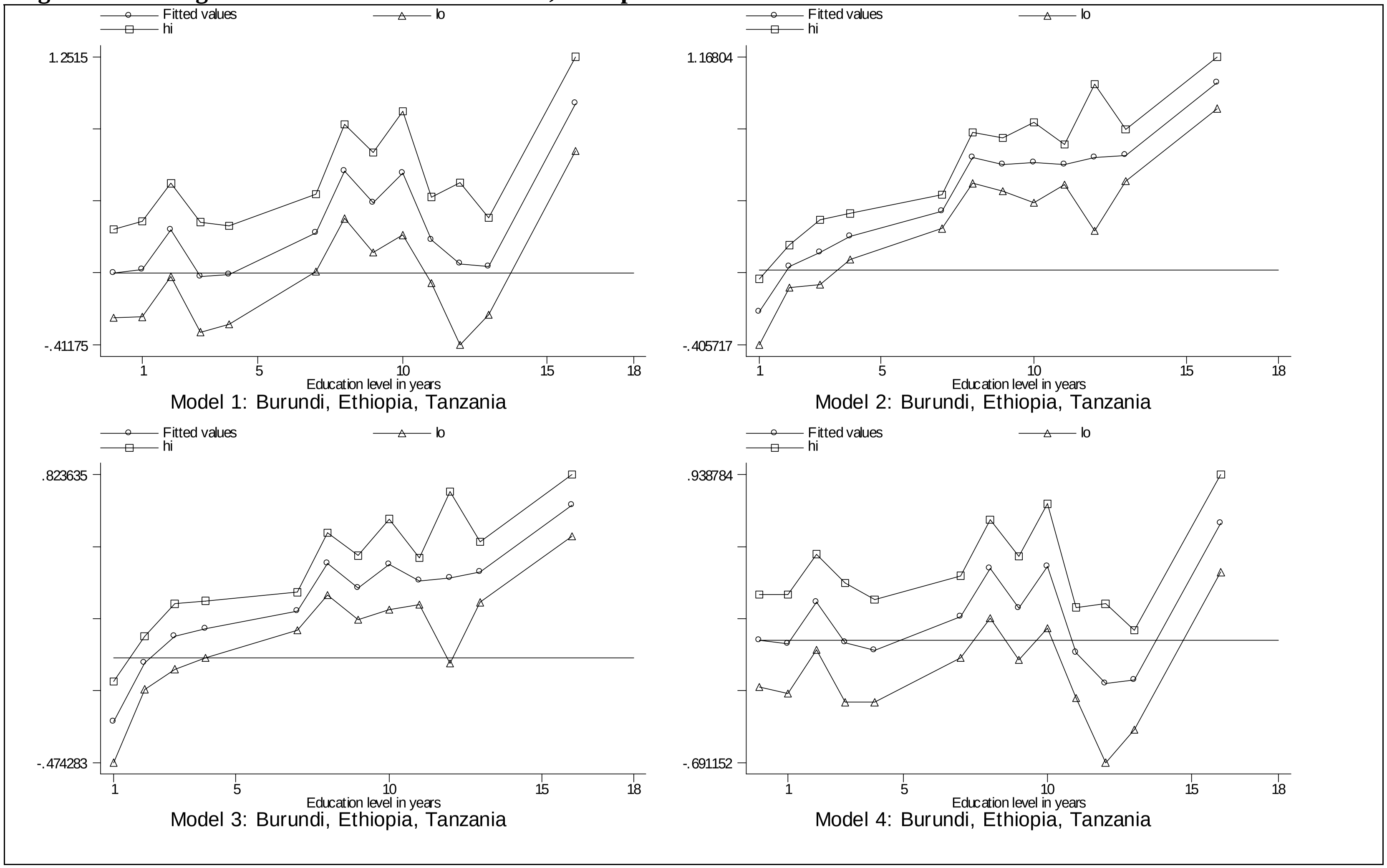
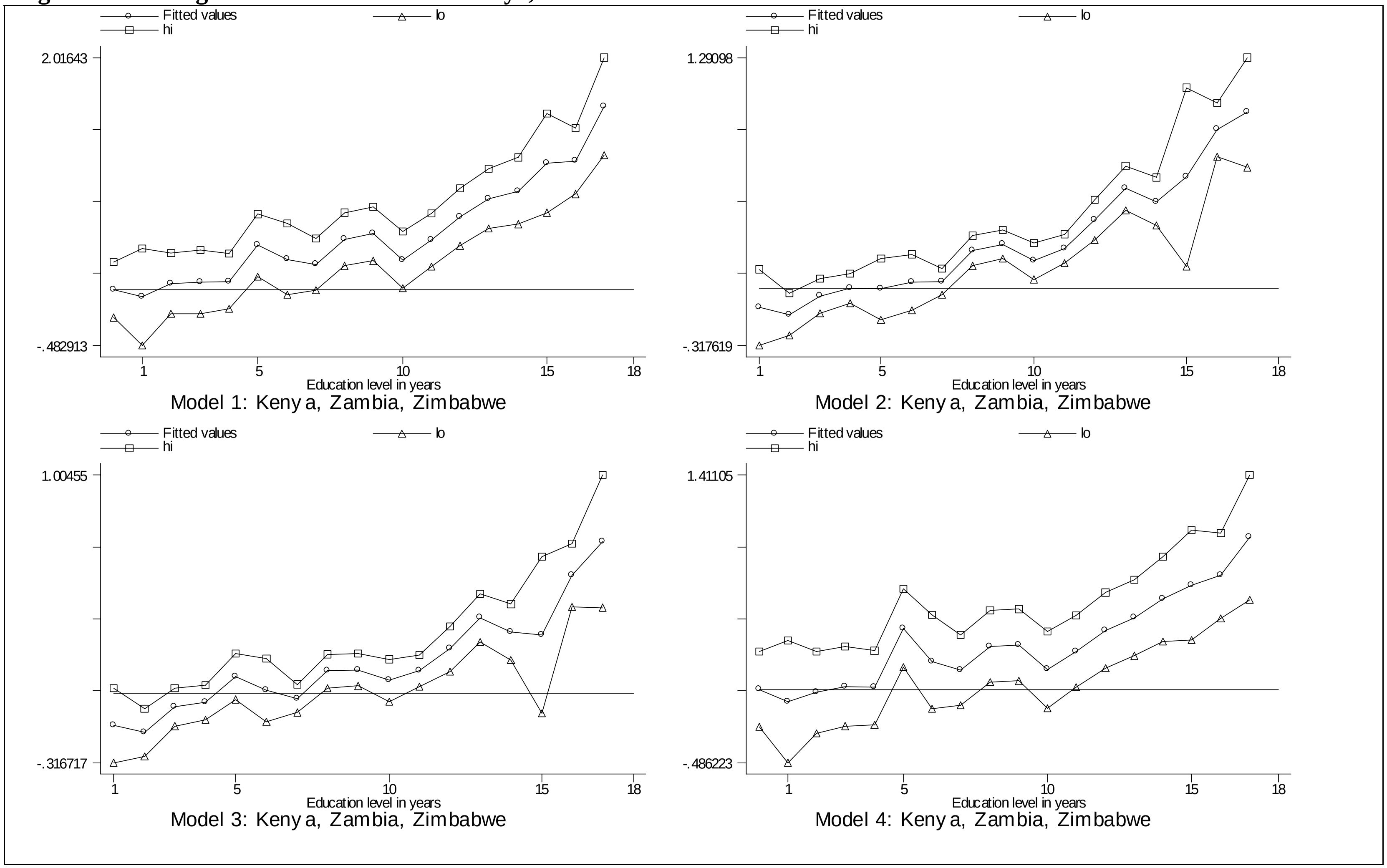


Figure 3: Earnings-Education Profiles in Kenya, Zambia and Zimbabwe – Models 1-4



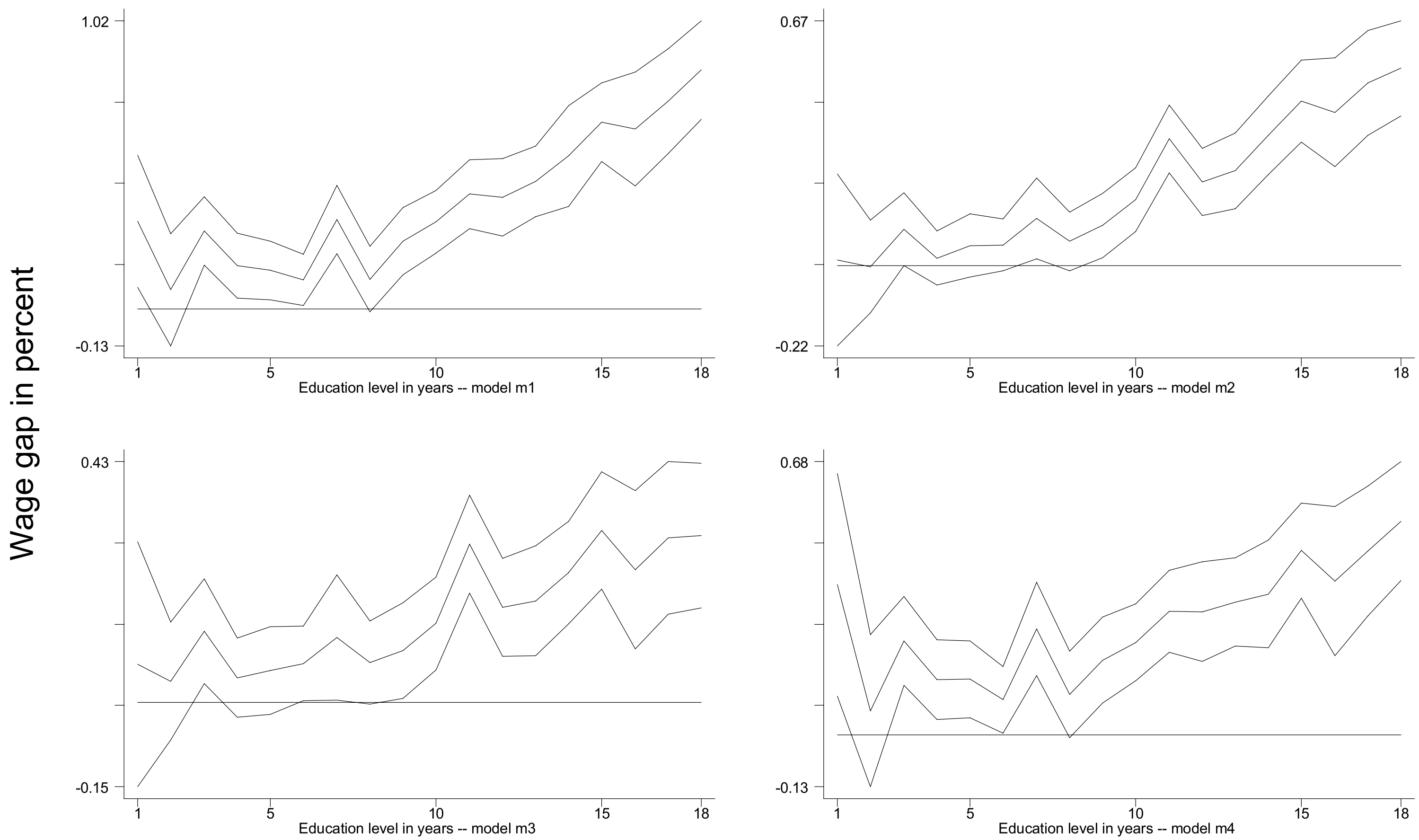


Figure 4. Earnings-Education Profiles in Algeria

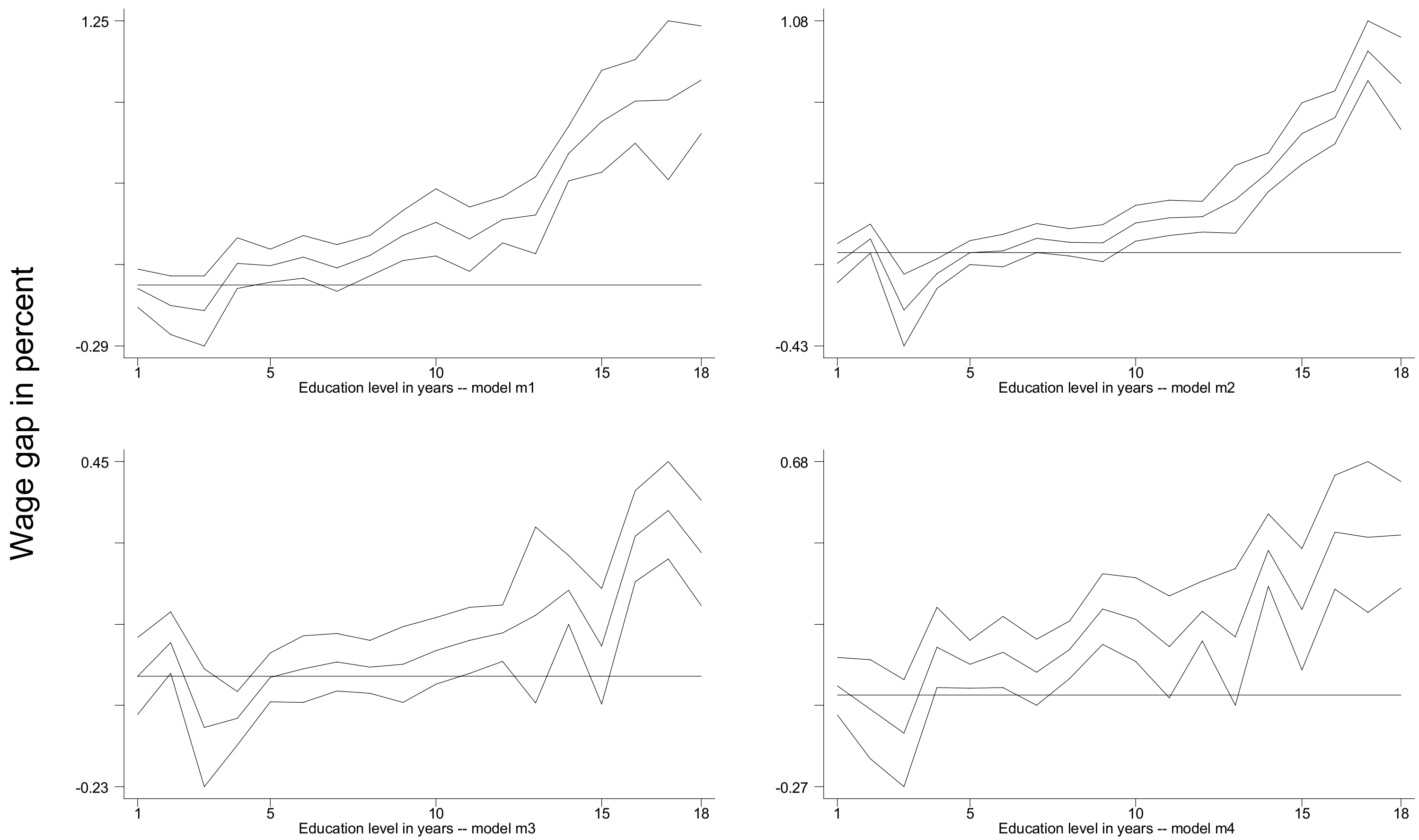


Figure 5. Earnings-Education Profiles in Morocco